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Abstract

This paper analyzes the effects of lagged changes in income inequality on credit growth and changes in housing prices. The theoretical model developed herein, borrowed heavily from Bengui and Phan (2016), predicts that growing income inequality should lead to credit growth and positive changes in housing prices. Using a panel dataset spanning 14 developed countries over 130 years, this model is tested empirically by applying first-difference ordinary least squares regressions with year and country fixed effects, as well as with lagged values for key predictive variables. The results indicate that income inequality is insignificant in predicting credit growth. However, lagged income inequality is significant in predicting changes in housing prices. Over the full sample, the fourth lag has a significantly positive coefficient. This result is robust through a battery of checks. The finding thus provides evidence for the hypothesis that growing inequality is associated with growing housing prices.

I. Introduction

2008, and the financial crisis that came with it, was a watershed year for economists in that it made clear the need to re-evaluate the current macroeconomic models concerning financial crises. Before then, movements in asset prices, especially booms and busts in housing prices, did not play a central role in most workhorse macro models, including most of the dynamic stochastic general equilibrium (DSGE) models employed by central banks. However, given the collapse of the housing bubble—which reached its peak in 2007 after several years of rampant speculation—and the subsequent deep recession, many now recognize that the activity in the financial sector can no longer be ignored from macroeconomic thinking. Indeed, Jorda et al. (2015) note, the seemingly unexpected nature of the 2008 global financial crisis was in fact due to the inability of current macroeconomic models to handle the rather prominent—and potentially dangerous—financial phenomenon, such as leveraged asset bubbles. This paper focuses on empirically documenting the empirical relationship between inequality, housing prices, and credit growth—specifically within the context of how the latter two contributed to the most recent financial crisis.

My results add to a quickly growing body of research which have sprung out of the Great Recession. Unsatisfied with the current models which failed to foresee the impending crisis, macroeconomists across the globe have become increasingly interested in developing models for what appears to several related trends: growing income inequality, risky asset bubbles, and increased leverage in the financial sector. Intuition, empirical data, and historical anecdotes—such as rising income inequality before the Great Depression of the 1930's—suggest that somehow inequality and financial markets are intertwined. Kumhof et al. (2014) develop a fairly simple mechanism by which a permanent, positive income shock to top earners leads to an increase in credit—that is, a credit boom. Similarly, Bengui and Phan (2016) develop a model in which increased earnings for top earners relative to bottom ones realizes increased asset prices. From these models and related stylized facts, several authors have further pursued empirical projects to evaluate the statistical relationship behind these key trends, as well as how they relate to economically-crippling financial crises. To that end, authors have tried to tie down various relationships, such as between crisis and credit growth, and credit growth and inequality. So far, the results are inconclusive. For instance, in Bordo and Meissner (2012), the authors find that growing inequality is insignificant in predicting either credit growth or financial crises, while in Kirschenmann et al. (2016), the authors find it is, at the very least, strongly correlated with the risk of financial crises. Meanwhile, in Jorda et al. (2015), the authors link housing bubbles to financial crises, and their results are made more robust when housing bubbles are concurrent with credit booms.

By exploring the three way relationship between inequality, credit, and housing prices more thoroughly and along different, unexplored dimensions, I submit this paper to the existing literature. Of specific contribution are my tests which account for additional lags of income inequality in predicting credit growth—which allows for a more thorough analysis of the relationship between changes in inequality and credit growth than what previous research has provided. Additionally, no other paper—at least to this author's knowledge—has tested the relationship between housing and income inequality, with more traditional macroeconomic factors used in such empirical tests. Given the housing bubble's role in many financial crises and its relationship with credit growth, this appears to be a sorely under-investigated relationship, which this paper hopes to remedy. All together, these two aspects of my research help paint a more panoramic view of the macroeconomy as it relates to credit, housing finance, and income inequality, in which the relationships among all three and the nuances which qualify them can now be described more thoroughly.

As a roadmap for this paper, the next section discusses related literature. Sections III and IV outline my theoretical and empirical models, respectively. Section V discusses my dataset. Sections VI and VII first present and then discuss my findings, with implications for my model, and for further research.

II. Review of Literature

The related literature around this topic is fairly extensive, but few clear cut answers have yet to emerge. Several authors, with the backing of historical and anecdotal evidence, have put together intricate yet pointed theoretical models which show associations between income inequality and credit growth and housing prices, respectively. Empirical analysis in the same vein suggest that there is some general relationship among these three variables—but to what extent and along what mechanism is not clear, as several authors find contradicting results. This empirical confusion has made it difficult to say in strong terms how, and to what extent, inequality impacts financial markets—a limitation this paper hopes to clear up.

Rajan, in his seminal book *Fault Lines* (2010), brings housing prices and credit together in a retelling of the events which led to the financial crisis of 2008. Using historical anecdotes from the United States, Rajan loosely describes a mechanism by which inequality leads to risky lending practices, housing and other asset bubbles, and ultimately a financial crisis. Due to the relative political popularity of providing housing credit over direct welfare, successive administrations instituted programs designed to increase home-ownership for poor people. In spite of the laudable intentions, this created an environment in which banks could lend to low-income people with some expectation or guarantee of government backing. Government regulators in Fannie Mae and Freddie Mac prioritize the administrations' housing efforts over financial regulation, readily buying mortgage securities which were becoming increasingly comprised of subprime mortgages. This only fueled the subprime mortgage lending even more, as lenders turned the corresponding securities into a quick profit. The positive loop of credit allowed the bubble to continue to grow on itself until 2008, when housing prices finally reached their apex and financial crisis kicked off.

Since 2010, much work has been done to encode this relationship into a refined theoretical model. One such paper, Kumhof et al. (2016), develops a comprehensive theoretical model which internalizes what the authors observe to be related trends of rising income inequality, rising debt-to-income ratios, and rising risk of financial crisis. All together, their model specifies the mechanisms by which high household leverage and financial crises are a result to changes in the distribution of income, in particular its concentration among high income households. The key to their model is the assumption that top earners, when given a boost in their income relative the bottom earners, do not spend all of it on consumption. Rather, they devote a large share of the increase to further increasing their financial wealth in the form of lending to poor households. Hence, in building their model, Kumhof et al. assume that top earners directly factor consumption and financial wealth into their utility functions—the result being that permanent income boosts give top earners an incentive to loan to the poor. The authors further assume that seek to minimize the drop in their consumption given a redistribution of income toward higher earners. Hence, they borrow from the rich. The effect of these two dynamics taken together is an unambiguous increase in the debt-to-income ratio when there is a change in income concentration favoring the rich. This results in an increase risk for financial crisis, which occurs when indebted households rationally choose to default.

Bengui and Phan (2016) tell a similar story, except they show how inequality leads to risky asset bubbles—and hence, the growth in price of assets such as housing. The authors develop a two-period, overlapping generations framework in which an agent's utility is a function of their consumption in both youth and old age. Agents can borrow and lend from one another and hold bubbly assets. Their model shows that as income of the rich increases relative to the poor, the price of assets increases, leading to bubbles. As will be discussed in the next section, a simplified version of this model will serve as the theoretical basis for my test.

In light of these theoretical publications, several authors have sought to test these key relationships empirically. Bertrand & Morse (2013) provide evidence for the positive relationship between inequality and credit. They do so by testing the relationship between the top earners' consumption and those at the bottom, much in the way that Kumhof et al. theorize. Not only do they find that they two groups' consumptions are positively correlated, but the middle income group's consumption is largely financed by credit—supporting the hypothesis. However, Bordo and Meissner (2013) test this relationship more directly—regressing credit growth on changes in income inequality—and find no relationship between the two. They build their model for credit growth around lagged changes in income inequality—as hypothesized by Kumhof et al.—as well as other more traditional macroeconomic variables which previous authors have found to be significant in predicting credit growth. One such predictor is current account deficit, as found by Mendoza and Terrones (2008). The hypothesized relationship is that the resulting inflow of foreign capital results in asset bubbles and an accompanying growth in credit. Another possible predictor Bordo and Meissner consider is economic growth, the rationale being that in periods of strong growth the mechanism which rein in credit growth are mitigated due to agents' optimism. Other predictors they consider include changes in the real interest rate and M2 money aggregate. Additionally, the authors consider a inequality and economic growth interaction term, with the rationale being that perhaps the effect of inequality on financial markets varies given the current economic condition—namely recession or expansion. For instance, perhaps the growing income inequality and economic growth of the mid-2000's had synergistic effects in creating the housing bubble. Bordo and Meissner find that changes in inequality and its accompanying interaction with GDP growth are not significant predictors for credit growth, while economic growth and changes in the real interest are.

Meanwhile Jorda et al. (2015) find evidence of the connection between asset bubbles and credit growth, as hypothesized by Rajan. They empirically show that the two often occur together and that, when they do, the result is generally a long, severe recession. The authors supplement this research with an additional paper published at the end of 2016, which shows that mortgages are increasing portion of financial institutions balance sheets—roughly doubling over the course of the 20th century. The key narrative is that housing and credit and inextricably linked in the current macroeconomy.

Interestingly, there are no papers—at least to the knowledge of this author—which seeks to empirically explore the relationship between inequality and asset prices such as housing. Though I will model both credit growth and changes in housing prices on inequality, the key contribution will be the discovery of the relationship—or lack thereof—between inequality and housing prices. However, past research has sought other means to explain movements in asset prices. For example, Bordo & Landon-Lane (2013) find that stock price booms are positively associated with housing prices, and Gali (2014) finds that low-interest rates tend to increase housing prices as well.

In guiding my empirical model and procedure, I rely on two papers: Schularick and Taylor (2012) and Kirschenmann et al. (2014). These papers use country-level fixed effects panel logit regression models to test the risk of a financial crisis based on several key macroeconomic variables. Though my dependent variables and estimation method are different than the aforementioned papers, their methodology and econometric procedure in working with the same dataset provide a useful starting point.

This dataset includes government debt, aggregate bank loans, M2 money supply, and so forth. To that end, they use essentially the same data set, the key difference being that Kirschenmann et al. also include data on the share of national income going to the top 1 percent of earners. Since I use essentially the same dataset as Kirschenmann et al. in my analysis—the only exception being the housing price variable—I will give a more comprehensive overview of the variables and the authors means of gathering them later in the Data section.

In their tests, Schularick and Taylor find that credit booms are indeed a significant predictor of financial crises. These results hold throughout different time period subsamples, with the inclusion of other variables, and in both ordinary least squares regressions and panel logit regressions. Furthermore, the authors used a variety of time fixed effects, country fixed effects, and robust standard errors to evaluate the robustness of their findings, and again find that credit booms and risk of financial crises are significantly and positively related.

Building off of those results, Kirschenmann et al. (2014) find that rising income inequality along with credit booms compound the risk of a financial crisis. They specify their models using panel logit regressions using country fixed effects and robust standard errors. They forego using time fixed effects in order to maintain an adequate amount of observations for their models. Lags of changes in equality are positively correlated with the risk of financial crises, both on their own and when included with the models specified in Schularick and Taylor concerning only credit booms. Additionally, the authors find that inequality has "unilateral" predictive power, even when controlling for several other known predictors of financial crisis and credit booms, such as current account deficit and value of real stocks. These results contradict the findings of Bordo and Meissner, in which the authors found that changes in income inequality were not significant in predicting either the risk of financial crisis or credit growth. Clarifying this relationship will be another hopeful goal of this paper.

III. Theoretical Model

My theoretical model is a simplified version of the one developed by Bengui and Phan. Through my construction of a simple utility maximizing equation in which consumption is a function of an individual's productivity and savings and lending choices, I show that increased inequality in the form of a growing gap between productivity has positive effects on both asset prices and credit.

I assume there exist two overlapping generations, the young and the old. Each agent is endowed with productivity, ω. ω can take two values: ω^{high} or ω^{low}. For simplicity, I assume that the share of the population with ω^{high} equals that with ω^{low}. Each young agent produces according to the function:

$$y = \omega n \tag{1}$$

where y is the value of the product he or she produces, ω is their productivity, and n is their supply of labor. For simplicity, I assume each agent inelastically supplies one unit of labor (n = 1). Thus, the distribution of income for young agents is:

$$F(\omega) = \omega \tag{2}$$

where F(ω) can take two possible values: ω^{high} or ω^{low}. I define those who earn ω^{high} as the rich and those who earn ω^{low} as the poor. The old do not produce, but rather receive a transfer payment equal to T.

Young agents may borrow and lend to one another, as well as buy bubbly assets. This is subject to the debt limit, $\bar{d} \geq 0$. Agents use bubbly assets as a store of value by buying it in their youth and then selling it the next period. The price of an asset in time t is given by B_t. For simplicity, I assume that bubbles are consistent—abstracting away from the real world risk of bubbly assets collapsing in price.

Thus, at time t with a given an asset price, B_t, and interest rate, R_t, an agent with productivity ω chooses debt position d_t and holds bubbly assets, x_t, to maximize lifetime utility:

$$\max_{d_t(\omega), x_t(\omega)} U\left(c_{y,t}(\omega), c_{o,t+1}(\omega)\right) = \ln\left(c_{y,t}(\omega)\right) + \beta\, c_{o,t+1}(\omega) \tag{3}$$

where $c_{y,t}(\omega)$ is consumption during an agent's youth and $c_{y,t+1}(\omega)$ is consumption during an agent's old age. I construct x_t as the fraction of the total supply of bubbly assets available such that for any particular agent, $0 \leq x_t \leq 1$. The concavity of the utility function with respect to $c_{y,t}(\omega)$ captures agents' incentive to borrow, lend and save. The linearity of $c_{y,t+1}(\omega)$ is constructed for simplicity's sake. This is subject to the budget constraints:

$$c_{y,t}(\omega) = \omega + \frac{d_t(\omega)}{R_t} - B_t x_t(\omega) \tag{4}$$

$$c_{o,t+1}(\omega) = T - d_t(\omega) + B_{t+1} x_t(\omega) \tag{5}$$

$$\text{where } 0 \leq x_t(\omega) \text{ and } d_t(\omega) \leq \bar{d}$$

I assume that all markets clear. To begin, if $d_t^r = d_t(\omega^{\mathrm{high}})$ is the amount the rich lend and the $d_t^p = d_t(\omega^{\mathrm{low}})$ is the amount the poor borrow, then

$$d_t^r + d_t^p = 0 \tag{6}$$

that is, the credit market clears. I further assume that this constraint is binding, so that in equilibrium $d_t^r = -\bar{d}$ and $d_t^p = \bar{d}$. Similarly,

$$\int c_{y,t}(\omega) + c_{o,t}(\omega)\,]dF(\omega) = \int \omega F(\omega) + \mathrm{T} \tag{7}$$

that is, the amount of consumption in the economy at time t is equal to its income. And lastly,

$$\int x_t(\omega)dF(\omega) = 1 \tag{8}$$

that is, the demand for bubbly assets equals the supply. I assume that in equilibrium that in equilibrium the rich lend and hold bubbly assets, while the poor borrow and do not hold any assets. Simply put then, $x_t(\omega^{\mathrm{high}}) = 1$.

This model produces the chief implication that:

Proposition 1: An increase in the concentration of income among the rich—that is, an increase in ω^{high}—is associated with an increase in the price of assets, B, as well as credit growth.

As a short proof, it can be shown that for a rich agent:

$$U'\left(c_{y,t}(\omega^{high})\right) = \beta \frac{B_{t+1}}{B_t} \tag{9}$$

which implies, according to the derivative of the utility function with respect to youth consumption, that:

$$B_t = \omega^{high} - \bar{d} - \frac{1}{\beta} \tag{10}$$

Thus, asset prices increase with inequality. Though credit and inequality does not factor directly, I rely on the related literature which shows the close relationship between housing and lending to extend my model to credit growth. (A more detailed proof of Equation 10 can be found in Appendix B.). This positive relationship between asset prices and inequality will be the key relationship I test for in my empirical model.

It should be briefly noted a simple rearranging of the terms in Equation (10) implies that income inequality is also a function of asset prices. This reverse causality makes intuitive sense as well, as one expect the capital gains from investing in financial markets in the real world to not be proportionally distributed across earners, but rather concentrated among the highest earners who use those assets as a means of storing wealth. Such reverse causality needs represents a problem from an empirical testing standpoint and will be addressed in the coming sections.

IV. Empirical Model

Following from the theoretical model presented above, I build to an empirical framework. The theoretical model shows that relative changes in the endowments for the rich and poor—income inequality—lead to changes in the size of the credit market and the price of risky assets. Accordingly, I use a first difference ordinary linear regression model which seeks to explain changes in the lending and housing prices on lagged changes in inequality. The reasons for using lagged changes in inequality are threefold. First, as indicated in my theoretical model as well as in the related literature, the full effect of a change in inequality should develop overtime—that is, a change in inequality in one year will not fully impact financial markets until some point in future. This makes sense intuitively, since we should not expect investors and speculators to react to such a macroeconomic shock instantaneously. Second, considering lagged values of independent variables reduces the effects of simultaneity one should expect among such macroeconomic variables as inequality, housing prices, and credit growth. Along a similar train of thought, this accounts in part for the reverse causality apparent in my theoretical model. And third, considering lagged of changes in income inequality allows for a more useful comparison to the related literature, in which the vast of similarly-focused empirical studies use lags.

I also include country fixed effects to account for enduring, country-specific heterogeneity across observations. As noted by Kirschenmann et al., this further implies that the coefficient estimates for credit growth and asset price change predictors are derived from their within-country variations, minimizing the impact of any potential biases due to differences in data reporting schemes or standards across countries. Furthermore, I include yearly fixed effects to control for period-specific trends in the global economy, such as the Great Depression. Since other macroeconomic variables—including the growth in real GDP, change in the value of stocks, change in the short-term interest rate, and percent change in the current account deficit—have been found to be significant in predicting credit growth and change in housing prices, I include a vector of other possible predictors to serve as a robustness check in estimating the effect of inequality changes on credit growth. Lastly, I include a vector to represent interactions term for change in inequality and growth in real GDP.

Thus, the preliminary model is as follows:

$$\%\Delta Y_{it} = \beta_0 + \sum_{j=1}^{P} \beta_j \left(\Delta Inequality_{i,t-j}\right) + \beta_{P+1} X_{i,t-1} + \beta_{P+2} Z_{i,t-1} + u_i + \delta_t + \varepsilon_{it} \qquad (11)$$

where Y is the dependent variable vector. For the first set of empirical tests, which will be explained further in the Empirical Procedure section, first Y is the percentage change in the value of real bank loans in country i at time t (credit growth). In the second set of tests, Y is the percent change in real housing prices. $(\Delta Inequality_{i,t-j})$ is lagged change in my measure of inequality in country i at time $t-j$ (change in inequality). As will be explained further, I consider some models contemporaneously depending on the estimation method in order to determine confidence in my specified model. u_i is the set of country fixed effects included in the linear models, δ_t is the set of time period indicator dummies, $X_{i,t-1}$ is the vector of control variable I include as a robustness check. These are growth in real GDP, change in the value of stocks, change in the short-term interest rate, and percent change in the current account deficit. To further analyze the effect of these predictors, it will be useful to consider an interaction term between lagged income inequality and lagged growth in real GDP per capita. As mentioned previously, one consideration in Bordo and Meissner is that perhaps the effect of inequality on credit growth differs depending on whether or not the economy is in recession or expansion. If such an interaction term were positive, then the effect of inequality is augmented in credit booms is augmented during economic expansions. $Z_{i,t-1}$ is this interaction term. ε_{it} is the error term.

By using a first differences model, I largely eliminate deterministic trends in the data, and so I assume each ε_{it} is normally distributed with mean zero. Furthermore, to account for autocorrelation within panels and cross-sectional correlation and heteroskedasticity across panel, I run tests in which I estimate my equation using generalized least squares models. I perform my estimates using robust standard errors to account for heteroskedasticity—that is, any changes in the variability of ε_{it} across time and countries.

V. Data

V.1. The Dataset

As stated previously, most of the dataset I am using was compiled by Oscar Jorda, Moritz Schularick, and Alan Taylor, and is pulled from their "Macrohistory" website. For my inequality metric, I use the share of income going to the Top 1 percent of households, as used in Kirschenmann et al.

The Jorda, Moritz, Schularick dataset contains panel data across 14 countries between the years 1870 and 2008. The countries included are: Australia, Canada, Denmark, France, Germany, Italy, Japan, the Netherlands, Norway, Spain, Sweden, Switzerland, the United Kingdom, and the United States.

The first key variable in this dataset is the aggregate value of bank loans, which Schularick and Taylor defined as, "the end-of-year amount of outstanding domestic currency lending by domestic banks to domestic households and nonfinancial corporations (excluding lending within the financial system)." Schularick and Taylor gather these observations themselves for each country, applying the most consistent standard possible across countries in including or excluding a financial institution as a "bank." Lending from informal institutions is not counted in this variable, both from the lack of accompanying data and the irregularities in defining such lending across countries. They note that any country-specific irregularities that could appear in these observations, as well as the effect of leaving out informal lending, are largely eliminated by applying county fixed effects.

The second key variable is a housing price index, normalized and with base 100 set in year 1990. This variable was constructed through extensive research, explained more fully in Knoll, Schularick, and Steger.

The distinguishing variable in the Kirschenmann et al. dataset is the share of national income going to the top 1 percent of households. The authors borrow this data from the World Wealth and Income Database (WWID), an ongoing project compiling time series data across countries on income and wealth distributions. These observations the same years and countries as the Jorda, Schularick, and Taylor data set and make working with the latter dataset fairly easy.

There are a variety of reasons I use the share of income going toward the very richest households as my metric of inequality, as opposed to a more traditional inequality index. Though synthetic indices, such as Gini or Theil coefficients, of inequality may provide a more comprehensive view of inequality for the population as a whole, the author note that WWID income data has several key advantages. First, is that the researchers at WWID apply a consistent methodology across countries in calculating the top income shares overtime, hence measurement errors in the inequality metric should be consistent across countries. Calculations of the synthetic indices rely on country-reported data and, sometimes, on differing methodologies, making it hard to guarantee consistent measurements across countries. The authors further note that the amount of data points afforded to them by using the income share of the top 1 percent of earners makes the variable much more attractive to use in empirical analysis than other metrics of inequality. Both of these indices have limited observations for even developed nations in our period of interest. And though these empirical justifications are useful, most important is the fact that a metric for the concentration of income better fits the story of my theoretical model. The dynamics of the theoretical model concern changes to the incomes of top earners—not necessarily the income of all earners. Hence, traditional inequality metrics abstract away from my theoretical model and make analysis of the empirical results less intuitive.

The Jorda, Moritz, Schularick dataset also includes other macroeconomic variables to use as control variables, per the related literature described in the last section. These include real and nominal gross domestic product (GDP) per capita, government debt, the short-term nominal interest rate on government securities, the consumer price index (CPI) with base year as 1990, the current account deficit as a percentage of real GDP, and indices of real stock market value compiled from Global Financial Data.

V.2. Transformations of Key Variables

Since I am estimating using a first differences model, I take first differences or the percent change over a one-year period for each of the key variables, depending on which is more applicable.

For value of bank loans, housing price index, GDP per capita, and stock value, I deflate them into real terms by using the CPI. Next, I take the first differences in their logs to derive the percent change. These transformed variables are what I use in my analysis.

I perform a similar procedure for my other key variables—the share of income to top 1 percent of households, the short-term real interest rate, and the current account deficit as a percent of GDP—but simply take the first differences. Deflating using the CPI is not applicable in these transformations.

V.3. Summary Statistics

Table 1 gives summary statistics for key variables percent change in lending, percent change in real housing prices, change in income for top 1 percent of households, percent change in real GDP per capita, change in real short-term interest rate, percent change in real stock value, and change in current account deficit as a percent of GDP. The table is divided into three parts:

the sample before 1945, after 1945, and the full sample, which provides a convenient means to see changes in the data over time.

Most readily apparent is how the number of observations grows from the Before 1945 sample to After 1945. For most variables, the change is subtle. However, for my key independent variable, the change is much pronounced—179 observations before 1945 versus 674 afterward—demonstrating most clearly the bulging nature of the data.

It is also important to note how the characteristic of most variables differ between the two subsamples. For instance, the mean value for the percent change in real stock value climbs from 0.014 to 0.065. Similarly, the standard deviation for change in short-term real interest rate in the pre-1945 sample is 0.061, where as it is only 0.025 in post-1945 subsample. Though such changes make sense and indicate readily-explainable changes to the structure of the global macroeconomy, they also represent an issue in how confident I can be in my estimations. To account for such wide swings in the behavior of the data, I take time fixed effects and run tests over smaller time period subsamples as a robustness check.

Table 2 and Table 3 report the estimation samples for credit growth and percent change in real housing price index, respectively. Both tables have three parts: pre-1945 subsample, post-1945 subsample, and full estimation sample. The estimation samples reveal how skewed data is, with roughly 500 of the over 600 observations in each estimation sample coming from the post-1945 subsample. Additionally, the issues with changing variable behavior over time appear to be made even more pronounced. As described previously, I have several strategies to deal with these issues empirically.

Tables 2 and 3 also reveal that the data is essentially the same in both estimation samples. Note that the mean and standard deviations for each of the variables present are essentially the same in both tables. This allows me to have confidence in my interpretation of the regression results, knowing that each set of tests for the specific dependent variable will be over essentially the same observations.

V.4. Benefits and Limitations of the Data

The advantages of using the Jorda, Schularick, and Taylor dataset is that it provides many data points across many countries and years. As shown in Tables 2 and 3, my estimation samples are quite large—with at least 500 observations in every test. Secondly, the dataset has been widely used by other economists in their research. Using the dataset myself allows to look to other papers as a benchmark for my tests and to which I can compare and contrast my results to help determine their validity.

However, there are also several key limitations with the dataset. As made abundantly clear in the summary statistics tables, the data tends to bulge over time, with more recent years carrying more data points. The downside of this is that outlier observations—such as those from the 1800's—are highly leveraged, and can skew the results of my analysis. I account for this somewhat in my tests by using time fixed effects. As a further robustness check, I take time period subsamples—running tests for data before 1945 and after—to see how the results change.

The second issue is that there are many missing data points, especially for income inequality. Not only does this temper the estimation sample, it means that some countries may have more weight in the regression results simply by having fewer missed observations. I account for this somewhat with country fixed-effects, but beyond that there is no other way to address this issue.

In the same vein as Kirschenmann et al. and Schularick and Taylor, there are two additional minor limitations with the data for which I account for. The first will be to drop the major war periods, namely 1914-1919 and 1939-1947. Dropping these extraordinary time periods has the duel benefit of making my analysis more representative of the prevailing story and for allowing me to compare my analysis with related papers. The second will be to drop bank loan data from France between 1870 and 1889 due to it being—as Schularick and Taylor describe—"noisy," with again the benefits being intuitive analysis of results and ability to compare my results to other papers.

VI. Empirical Results

Recall that the empirical model is as follows:

$$\%\Delta Y_{it} = \beta_0 + \sum_{j=1}^{P} \beta_j \left(\Delta Inequality_{i,t-j}\right) + \beta_{P+1} X_{i,t-1} + \beta_{P+2} Z_{i,t-1} + u_i + \delta_t + \varepsilon_{it} \qquad (11)$$

The first step is to establish is confidence in my specified model. My goal is to consider up to several lags of income inequality in predicting changes in credit and housing prices using an ordinary least squares model with time and country fixed effects. However, given an unbalanced panel data set that bulges overtime, I need further confidence that the results given a particular estimation method are robust.

I do this by comparing estimated coefficient for predictors across several estimation methods—some of which can only be modeled using contemporaneous variables. Accordingly, for my first set of tests I do not include any lags. As a baseline, I first consider an ordinary least squares model with time-fixed effects. I build on this first model by including, first, country random effects, and then county fixed effects. The fourth estimation model attempts to account for my unbalanced panel dataset and autocorrelated disturbances. The fifth and sixth specifications consider a possible heteroskedastic error structure and autocorrelation within panels—with the fifth model considering a common autocorrelation and the sixth considering country-specific autocorrelation. Lastly, I use a generalized method of moments estimator to account for correlation between the dependent variable and its lags. If the estimated coefficients for my predictors are consistent, I can have confidence in my fixed effects model with lags. Since I am considering two dependent variables, I run these tests twice—one in which the dependent variable is credit growth, and the other in which it is changes in real housing prices.

Table 4 reports the estimates for predicting credit growth on the contemporaneous changes in income inequality as well as several control variables, per the methodology described above. The coefficients for every variable are relatively consistent across each estimation method, and their significance essentially the same throughout. The coefficient for change in income inequality varies between 0.003 and 0.009, with this number being slightly significantly different from zero in just two of the seven specifications. The control variables—real GDP growth, change in real stock value, change in short-term real interest rate, and change in current account deficit—display similar consistency. The magnitude of a variable varies by only a few thousandths, and its significance is unchanged save for a few models. The only noteworthy exceptions are the significance of the change of real stock value—which is highly significant in every model except the OLS methods using country random fixed and country fixed effects—and the change in current account deficit, which is significant in every model except in the GMM model. With the key independent variable displaying a consistent estimated coefficient across models and the control variables, for the most part, duplicating this behavior, I conclude the OLS specification of my model with time and country fixed effects is reasonable and have confidence in predicting credit growth using lags of changes in income inequality.

Next, I repeat the tests described above but with changes in real housing prices as the dependent variable. Table 5 reports the results for estimating this variable using contemporaneous predictors across several specifications. These results are slightly more nuanced than the results in predicting credit growth, but my model appears to still be correctly specified in that the same relationship between inequality and housing prices appears to unfold across the battery of estimation methods. For instance, the coefficient for a contemporaneous change in income inequality varies from -0.006 to 0.000, and is insignificant in each of the seven estimation methods. This coefficient has a much higher magnitude in the OLS methods than it is in the GLS or GMM methods, where it is essentially zero. Similarly, coefficients for the control variables are essentially the same in the OLS methods before shifting in the GLS and GMM methods. Though these represent a possible issue in my ability to model my specification using OLS and lags, the fact that the significance of these coefficients is—with just one exception—the same throughout indicates that, though the exact effect of income inequality on housing prices may differ depending on the estimation method, the same story is being told in each one. The single exception is the significance of the change in real stock value, which goes from insignificant in the OLS methods to highly significant in the GLS and GMM models. I conclude that estimating using an OLS model with time and country fixed effects in order to consider lags is reasonable.

Given this confidence, the next step is to determine the appropriate number of lags for change in income inequality. I do so following the methodology used in Kirschenmann et al. First, the authors assume at most six lags. If the coefficient for the sixth lag is not statistically significant, then they remove that lag and test with five lags. They repeat this process until the coefficient of the largest lagged variable is significant. I do this test for both models predicting both credit growth and changes in real housing prices and do not assume that the optimal number of lags is the same for both. To account for invariant, cross-country heterogeneity and structural changes to the world macroeconomy over time, my model models consider both country and year fixed effects.

Table 6 reports the regression results for predicting credit growth on lags income inequality and control variables. In completing the Kirschenmann et al optimal lag methodology as described previously, I find that there is no optimal number of lags for income inequality when assuming at most six lags are feasible. Not only was no combination of lags optimal, but no lag in any test was significant. In the name of completeness, I adjust the methodology and assume up to 10 lags of income inequality could be optimal and find the same result. The fact that no lags between one and 10 were significant strongly suggest that changes in income inequality and credit growth are unrelated, which do not support the first half of my hypothesis relating credit growth and income inequality.

Regardless, for the sake of presentation, Table 6 models credit growth on four lags of income inequality, along with my specified control variables as previously discussed in my empirical model section. Additionally, using four lags will provide a useful comparison to results estimating changes in real housing prices on lagged income inequality, about which more will be discussed shortly. Column (1) is the basic model, as described by Equation (11). Column (2) adds a GDP-inequality interaction term, which allows us to see how macroeconomic conditions effect the relationship between income inequality and financial markets. Namely, whether the economy is in recession or expansion has any significance on my empirical tests. Column (3) estimates the same model as Column (2), but considers only observations coming from the post-195 subsample as a robustness check. As alluded to earlier, the dataset tends to bulge overtime in that there are drastically more data points for variables such as the top 1 percent's share of income and the short-term real interest rate. Additionally, the characteristics of these variables, including their means and standard deviations, are significantly different between the period before 1945 and the period after 1945. Hence, the results of my model estimated using post-1945 subsample helps determine what effect, if any, this disparity in the distribution of data points has on my model. Not only does account for bulging, it also is useful to track possible structural changes in the global economy and to see how these macroeconomic variables behave in a more current era.

As seen in Table 6, the coefficients for the inequality lags are nearly zero and at no reasonable level of confidence are they significant, meaning that credit growth and inequality have no apparent association. Meanwhile, the control variables have vastly more predictive power, with lagged real GDP growth, change in interest rate, and change in current account deficit being highly significant. This confirms much of what the related literature has found, in which positive changes in GDP growth, the current account deficit, and interest rates are associated with delayed changes in credit growth. However, contrary to some of the other related literature, the value of real stock and credit growth do not appear to be associated with one another, as the accompanying coefficient for the change in the real stock value is near zero in Columns (1), (2), and (3). The interaction term between real GDP growth and income inequality, as seen in Column (2), is not significant. This suggests that the effect of inequality on credit growth is the same, no matter if the economy is growing or receding.

The post-1945 time period subsample tells essentially the same story. Though the magnitude of the coefficients change some in the subsample, the significance predictors are essentially the same in Column (3) and they are in Columns (1) or (2). In particular, lagged income inequality remains insignificant in predicting credit growth—whether estimating the full sample or the post-1945 subsample.

In short, lagged changes of income inequality are not associated with credit growth. This result is consistent across several considered lag values, as well as with and without an interaction term with GDP growth. These results do not support the first part my hypothesis relating income inequality and credit growth.

Table 7 reports the results of the same tests estimating the change in real housing prices on lagged changes in income inequality. As it was before, three models are estimated: Column (1) models lagged income inequality and control variables, Column (2) adds the GDP-inequality interaction term, and Column (3) considers the post-1945 subsample as a robustness check. Using the Kirschenmann et al. methodology, I determine that the optimal number of lags is four. Accordingly, it can be seen in Columns (1) and Column (2) that the fourth lag of the change in income inequality is significant in predicting changes in real housing prices, with a one percent increase in the Top 1% of household's share of income leading to, approximately, a 0.02 percent increase in housing prices. Lags one through three of income inequality are insignificant, meaning they are not associated with housing prices. Real GDP growth and percent change in the value of real stocks are significant, while interestingly changes in the interest rate, current account deficit, and the GDP-inequality interaction term are not. The fact that the significance of the control variables differs so widely in the credit growth tests versus the change in housing prices tests indicates is another indication that the two are not strongly linked as hypothesized. Regardless, the significance of income inequality in predicting changes in housing prices validates, at least in part, my hypothesis.

These results are only strengthened by the robustness check conducted in Column (3), in which I estimate over only the post-1945 subsample. Using these more recent data points, both the second and fourth lags of changes in income inequality are significant. In particular, a one percent increase in the Top 1% of household's share of income is associated with a 0.01 percent increase in housing prices two years later, and a 0.02 percent increase four year later. The significance of the control variables remain generally unchanged. The only exception is the GDP-inequality interaction term, which becomes significant and positive in the post-1945 subsample. This implies that, in the current era, that economic growth exacerbates effect of growing income inequality on housing prices.

As a final robustness check, I model credit growth and changes in real housing prices on lagged changes in income inequality and other control variables simultaneously over the same estimation sample. Doing so ensures adds clarity to how the independent relationships between inequality and credit and inequality and housing prices play out over the same years of observations. This in turn, allows me to interpret how inequality impacts financial markets in general, which is the goal of my theoretical model and paper.

In keeping with previous tests, I estimate this model using four lags of income inequality. Table 8 reports these results. Over the same estimation sample, the effect of income inequality on housing prices and credit growth are the same as when modeled separately. None of the four lags of income inequality are significant in predicting credit growth, with each coefficient being essentially zero. Meanwhile, in predicting changes in housing prices, the fourth lag of income inequality is significant and has the same magnitude as previously found, 0.020. The significance of the control variables differ depending on the dependent variable. These results reaffirm that changes in housing prices and credit growth as a function of income inequality appear to be unrelated. As to why this is the case is not immediately clear. However, more about this will be discussed in the Conclusion section.

VII. Conclusion

Using a first-differences OLS model with year and country fixed effects, I find that lags of income inequality—in the form of an increased concentration of national income among the top 1 percent of households, is significant in predicting increasing in real housing prices, but not significant in predicting credit booms. In particular, a one percent increase in the top 1 percent households' income is associated with a 0.02 percent increase in housing prices four years later. This result accounts for the impact of other factors—such as real GDP growth, changes in the real short-term interest rate, changes in stocks' real value, and changes in the current account deficit—as specified by the related literature as significant in moving asset prices, credit, or both. Additionally, the result is robust over time period subsamples, remaining consistent in significance and magnitude. In fact, an additional lag of income inequality becomes significant in predicting housing price changes when looking at post-1945 observations—in particular, changes in income of the Top 1% are associated with changes in housing price two years later. Meanwhile, the impact of lagged income inequality on credit growth is close zero and insignificant across specifications. I have confidence in my OLS estimations based on the consistency of my empirical model across estimation methods when modeled contemporaneously. However, my results are limited in that reverse causality is may still exist in my finding. I account for them in part by using only lagged values for independent variables in my key tests, but the feedback loop between asset prices and inequality would overstate the significance of my results. Though my results are encouraging in that they are robust over a battery of checks, more advanced testing is needed to confirm their significance.

The results confirm, in part, my hypothesis and theoretical model which sought to explain movements in housing prices and credit through changes in income inequality. My model is successful in predicting increases in housing prices as a result of growing income inequality. This confirms the intuition that the rich use housing and other bubbly assets as a store of wealth, and that an increasingly top heavy income distribution will fuel asset price booms. This result adds to a growing body of work seeking to explain housing price movements in the context of risky asset bubbles and their impact on macroeconomic health. The model fails in that the link between credit and housing appears to be not as direct as thought by myself and others. Indeed, the results of simultaneous test indicate that very different mechanisms must be at play between credit and asset prices, as the estimation results for income inequality on credit growth and changes in real housing prices remain persistent. The exact story unfolding in the data remains, at least in part, hidden, making it hard to describe the exact mechanisms at play.

These findings open the door to explore some very interesting questions. If credit and housing prices are not inextricably linked as hypothesized by myself and others, than why do they play a concurrent role in financial crises, as found by Jorda et al. (2015)? If income inequality can drive housing bubbles but not credit booms, then what other factor is at play? And as for my results in particular, it is interesting to explore why the only the fourth lag is robust. What is the mechanism that delays income inequality's impact by four years on housing prices? And, of course income inequality is itself likely a symptom of some other macroeconomic phenomenon—is my result just another link in a long, hidden chain of mechanisms? These questions and others like them will surely be answered as economists seek a deeper understanding of the macroeconomy.

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Appendix A – Tables

1. Summary Statistics

Table 1: Descriptive statistics for key variables over the full sample. Data divided into two time period subsamples (before and after 1945).

Before 1945	**N**	**Mean**	**S.D.**	**Min**	**Max**
%Δreal bank loans	665	0.041	0.094	-0.426	0.683
%Δreal housing price index	543	0.011	0.085	-0.350	0.373
Δ Top 1%'s income	179	-0.091	1.033	-5.960	3.200
%Δ real GDP per capita	868	0.015	0.045	-0.261	0.162
Δ real short-term interest rate	664	0.000	0.061	-0.306	0.366
%Δ real stock value	795	0.014	0.172	-0.796	0.980
Δ Current Account Deficit (% of GDP)	761	0.000	0.029	-0.246	0.204
After 1945	**N**	**Mean**	**S.D.**	**Min**	**Max**
%Δreal bank loans	832	0.065	0.072	-0.167	0.601
%Δreal housing price index	783	0.026	0.083	-0.382	0.076
Δ Top 1%'s income	674	0.013	0.606	-8.740	4.960
%Δ real GDP per capita	854	0.027	0.025	-0.067	0.167
Δ real short-term interest rate	682	0.000	0.025	-0.139	0.136
%Δ real stock value	1122	0.065	0.221	-2.223	0.999
Δ Current Account Deficit (% of GDP)	787	0.001	0.021	-0.186	0.203
Total	**N**	**Mean**	**S.D.**	**Min**	**Max**
%Δreal bank loans	1497	0.054	0.083	-0.426	0.683
%Δreal housing price index	1326	0.020	0.084	-0.382	0.756
Δ Top 1%'s income	853	-0.008	0.717	-8.740	4.960
%Δ real GDP per capita	1722	0.021	0.037	-0.261	0.167
Δ real short-term interest rate	1346	0.000	0.046	-0.306	0.366
%Δ real stock value	1917	0.044	0.203	-2.223	0.999
Δ Current Account Deficit (% of GDP)	1548	0.001	0.025	-0.246	0.204

Notes: N is observations. S.D. is standard deviation. Min is the minimum value that a variable takes in the current sample. Max is the maximum value that a variable takes in the current sample.

Table 2: Descriptive statistics for key variables for the estimation sample for credit growth analysis. Data divided into two time period subsamples (before and after 1945).

Before 1945	**N**	**Mean**	**S.D.**	**Min**	**Max**
%Δreal bank loans	132	0.025	0.095	-0.320	0.341
Δ Top 1%'s income	132	-0.017	0.827	-2.000	2.150
%Δ real GDP per capita	132	0.013	0.049	-0.148	0.162
Δ real short-term interest rate	132	0.001	0.078	-0.203	0.366
%Δ real stock value	132	0.003	0.227	-0.796	0.452
Δ Current Account Deficit (% of GDP)	132	0.001	0.032	-0.010	0.147
After 1945	**N**	**Mean**	**S.D.**	**Min**	**Max**
%Δreal bank loans	510	0.061	0.685	-0.157	0.392
Δ Top 1%'s income	510	0.043	0.617	-8.740	4.960
%Δ real GDP per capita	510	0.024	0.022	-0.043	0.114
Δ real short-term interest rate	510	0.001	0.025	-0.139	0.135
%Δ real stock value	510	0.078	0.199	-0.898	0.860
Δ Current Account Deficit (% of GDP)	510	0.001	0.016	-0.118	0.094
Total	**N**	**Mean**	**S.D.**	**Min**	**Max**
%Δreal bank loans	642	0.054	0.076	-0.320	0.392
Δ Top 1%'s income	642	0.031	0.665	-8.740	4.960
%Δ real GDP per capita	642	0.022	0.030	-0.148	0.162
Δ real short-term interest rate	642	0.001	0.042	-0.203	0.366
%Δ real stock value	642	0.062	0.207	-0.798	0.860
Δ Current Account Deficit (% of GDP)	642	0.001	0.020	-0.118	0.146

Notes: N is observations. S.D. is standard deviation. Min is the minimum value that a variable takes in the current sample. Max is the maximum value that a variable takes in the current sample.

Table 3: Descriptive statistics for key variables for the estimation sample for change in housing price analysis. Data divided into two time period subsamples (before and after 1945).

Before 1945	**N**	**Mean**	**S.D.**	**Min**	**Max**
%Δ real housing price index	103	0.002	0.098	-0.299	0.279
Δ Top 1%'s income	103	-0.028	0.802	-2.000	2.140
%Δ real GDP per capita	103	0.011	0.047	-0.148	0.126
Δ real short-term interest rate	103	0.003	0.081	-0.203	0.366
%Δ real stock value	103	0.002	0.205	-0.796	0.452
Δ Current Account Deficit (% of GDP)	103	0.002	0.031	-0.010	0.146
After 1945	**N**	**Mean**	**S.D.**	**Min**	**Max**
%Δ real housing price index	511	0.028	0.076	-0.382	0.272
Δ Top 1%'s income	511	0.044	0.616	-8.740	4.960
%Δ real GDP per capita	511	0.024	0.022	-0.043	0.115
Δ real short-term interest rate	511	0.001	0.025	-0.139	0.136
%Δ real stock value	511	0.078	0.199	-0.798	0.860
Δ Current Account Deficit (% of GDP)	511	0.001	0.016	-0.118	0.094
Total	**N**	**Mean**	**S.D.**	**Min**	**Max**
%Δ real housing price index	614	0.024	0.081	-0.382	0.279
Δ Top 1%'s income	614	0.032	0.651	-8.740	4.960
%Δ real GDP per capita	614	0.022	0.028	-0.148	0.126
Δ real short-term interest rate	614	0.001	0.040	-0.203	0.366
%Δ real stock value	614	0.065	0.202	-0.798	0.860
Δ Current Account Deficit (% of GDP)	614	0.001	0.019	-0.118	0.146

Notes: N is observations. S.D. is standard deviation. Min is the minimum value that a variable takes in the current sample. Max is the maximum value that a variable takes in the current sample.

2. Estimates

Table 4: Contemporaneous modeling of credit growth on changes in income inequality + other control variables.	(1) OLS	(2) Random Effects	(3) Fixed Effects	(4) Fixed Effects + Autocorrelation	(5) GLS + Common Autocorrelation	(6) GLS + Country-Specific Autocorrelation	(7) GMM
Δ Top 1%'s income	0.005 (0.005)	0.005 (0.005)	0.005 (0.005)	0.007* (0.004)	0.003 (0.003)	0.003 (0.002)	0.009* (0.005)
%Δ real GDP per capita	0.750*** (0.128)	0.750*** (0.084)	0.719*** (0.083)	0.560*** (0.094)	0.599*** (0.084)	0.630*** (0.082)	0.589*** (0.085)
Δ real short-term interest rate	0.418*** (0.099)	0.418*** (0.039)	0.406*** (0.040)	0.444*** (0.054)	0.395*** (0.055)	0.380*** (0.055)	0.660*** (0.053)
%Δ real stock value	0.034* (0.020)	0.034 (0.031)	0.033 (0.032)	0.038*** (0.013)	0.027** (0.011)	0.024** (0.010)	0.037** (0.018)
Δ Current Account Deficit (% of GDP)	-0.379*** (0.143)	-0.379** (0.148)	-0.397** (0.146)	-0.340*** (0.123)	-0.460*** (0.103)	-0.466*** (0.095)	-0.251 (0.194)
%Δ L1.real bank loans							0.369*** (0.042)
N	642	642	642	629	642	642	614
R-squared	0.429		0.431				
Adjusted R-squared		0.429	0.426	0.173			

Notes: Dependent variable is the annual percent change in real bank loans. Δ denotes annual difference. Columns (1), (2), (3), and (4) are estimated by OLS. Random effects denotes country random effects. Fixed effects denotes country fixed effects. Autocorrelation (Columns (4), (5), and (6)) denotes that those estimation method accounts for autocorrelation in the dependent variable. Columns (5) and (6) are estimated by GLS. Column (7) estimated by GMM. Coefficients reported in first row and standard errors reported below in parenthesis. *** indicates significance at 99% confidence; ** at 95% confidence, and * at 90% confidence. Time fixed effects used in Columns (1), (2) and (3)--results not reported. Robust standards used in Columns (1), (2), (3), and (7).

Table 5: Contemporaneous modeling of changes in real housing prices on changes in income inequality + other control variables.	(1) OLS	(2) Random Effects	(3) Fixed Effects	(4) Fixed Effects + Autocorrelation	(5) GLS + Common Autocorrelation	(6) GLS + Country-Specific Autocorrelation	(7) GMM
Δ Top 1%'s income	-0.006 (0.004)	-0.006 (0.004)	-0.005 (0.004)	-0.001 (0.004)	-0.003 (0.003)	-0.002 (0.003)	0.000 (0.002)
%Δ real GDP per capita	0.952*** (0.159)	0.952*** (0.195)	0.939*** (0.229)	0.468*** (0.116)	0.442*** (0.085)	0.440*** (0.083)	0.576** (0.252)
Δ real short-term interest rate	0.393*** (0.120)	0.393*** (0.082)	0.382*** (0.084)	0.452*** (0.059)	0.418*** (0.054)	0.419*** (0.048)	0.526*** (0.100)
%Δ real stock value	0.005 (0.023)	0.005 (0.030)	0.005 (0.029)	0.028** (0.014)	0.034*** (0.012)	0.030*** (0.012)	0.038** (0.017)
Δ Current Account Deficit (% of GDP)	-0.559*** (0.197)	-0.559*** (0.118)	-0.570*** (0.126)	-0.472*** (0.139)	-0.346*** (0.121)	-0.375*** (0.121)	-0.533** (0.225)
%Δ L1.real housing price index							0.390*** (0.081)
N	614	614	614	601	614	614	586
R-squared	0.377		0.380				
Adjusted R-squared		0.377	0.368	0.123			

Notes: Dependent variable is the annual percent change in real housing prices. Δ denotes annual difference. Columns (1), (2), (3), and (4) are estimated by OLS. Random effects denotes country random effects. Fixed effects denotes country fixed effects. Autocorrelation (Columns (4), (5), and (6)) denotes that those estimation method accounts for autocorrelation in the dependent variable. Columns (5) and (6) are estimated by GLS. Column (7) estimated by GMM. Coefficients reported in first row and standard errors reported below in parenthesis. *** indicates significance at 99% confidence; ** at 95% confidence, and * at 90% confidence. Time fixed effects used in Columns (1), (2) and (3)--results not reported. Robust standards used in Columns (1), (2), (3), and (7).

Table 6: Modeling credit growth on lagged changes in income inequality + other control variables. Post-1945 subsample modeled in Column 3.	(1) Inequality Lags + Control Variables	(2) Interaction Term Added	(3) Post-1945 Subsample
ΔL1. Top 1%'s income	0.002 (0.002)	-0.001 (0.003)	-0.019 (0.019)
ΔL2. Top 1%'s income	0.001 (0.004)	0.001 (0.004)	-0.003 (0.005)
ΔL3. Top 1%'s income	-0.003 (0.006)	-0.004 (0.006)	-0.006 (0.007)
ΔL4. Top 1%'s income	0.000 (0.005)	0.000 (0.005)	-0.003 (0.006)
%ΔL1. real GDP per capita	0.740*** (0.105)	0.726*** (0.102)	1.014*** (0.178)
ΔL1. real short-term interest rate	0.369*** (0.078)	0.362*** (0.080)	-0.028 (0.087)
%ΔL1. real stock value	0.007 (0.027)	0.009 (0.026)	0.013 (0.031)
ΔL1. Current Account Deficit (% of GDP)	0.319*** (0.098)	0.316*** (0.102)	0.273 (0.184)
%Δ L1.Top 1% * L1.%Δ real GDP		0.146 (0.209)	0.936 (1.038)
N **R-squared** **Adjusted R-squared**	595 0.407 0.392	595 0.408 0.392	482 0.371 0.351

Notes: Dependent variable is the annual percent change in real bank loans. Δ denotes annual difference. Estimation is by OLS. Coefficients reported in first row and standard errors reported below in parenthesis. *** indicates significance at 99% confidence; ** at 95% confidence, and * at 90% confidence. Time fixed-effects, country fixed-effects, and robust standard errors used in both models. Models specifying up to six lags of income inequality were also estimated. Those results are similar to those reported above and were not included in this table.

Table 7: Modeling changes in real housing prices on lagged changes in income inequality + other control variables. Post-1945 subsample modeled in Column 3.	(1) Inequality Lags + Control Variables	(2) Interaction Term Added	(3) Post-1945 Subsample
ΔL1. Top 1%'s income	-0.002 (0.006)	-0.008 (0.010)	-0.006 (0.006)
ΔL2. Top 1%'s income	0.002 (0.008)	0.002 (0.007)	0.010* (0.006)
ΔL3. Top 1%'s income	-0.004 (0.005)	-0.005 (0.005)	0.006 (0.007)
ΔL4. Top 1%'s income	0.020* (0.010)	0.019* (0.010)	0.019** (0.007)
%ΔL1. real GDP per capita	0.891** (0.030)	0.903*** (0.283)	1.357*** (0.269)
ΔL1. real short-term interest rate	-0.020 (0.165)	-0.035 (0.168)	-0.233 (0.207)
%ΔL1. real stock value	0.070*** (0.022)	0.071*** (0.020)	0.057*** (0.018)
ΔL1. Current Account Deficit (% of GDP)	-0.137 (0.146)	-0.125 (0.149)	-0.098 (0.138)
%Δ L1.Top 1% * L1.%Δ real GDP		0.317 (0.383)	0.586* (0.300)
N **R-squared** **Adjusted R-squared**	568 0.364 0.349	568 0.368 0.353	482 0.407 0.390

Notes: Dependent variable is the annual percent change in real housing prices. Δ denotes annual difference. Estimation is by OLS. Coefficients reported in first row and standard errors reported below in parenthesis. *** indicates significance at 99% confidence; ** at 95% confidence, and * at 90% confidence. Time fixed-effects, country fixed-effects, and robust standard errors used in both models. Models specifying up to six lags of income inequality were also estimated. Those results are similar to those reported above and were not included in this table.

Table 8: Simultaneously modeling credit growth and changes in real housing prices on lagged changes in income inequality + control variables	(1) Credit growth	(2) Changes in real housing prices
ΔL1. Top 1%'s income	-0.001 (0.005)	-0.008 (0.006)
ΔL2. Top 1%'s income	0.001 (0.005)	0.002 (0.005)
ΔL3. Top 1%'s income	-0.004 (0.006)	-0.005 (0.007)
ΔL4. Top 1%'s income	-0.001 (0.006)	0.019*** (0.007)
%ΔL1. real GDP per capita	0.814*** (0.128)	0.903*** (0.143)
ΔL1. real short-term interest rate	0.356*** (0.081)	-0.035 (0.091)
%ΔL1. real stock value	0.018 (0.017)	0.071*** (0.019)
ΔL1. Current Account Deficit (% of GDP)	0.338** (0.142)	-0.125 (0.159)
%Δ L1.Top 1% * L1.%Δ real GDP	0.173 (0.156)	0.317* (0.175)
N **R-squared** **Adjusted R-squared**	568	

Notes: Dependent variable in Column (1) is the annual percent change in real bank loans. Dependent variable in Column (2) is the annual percent change in real housing prices. Δ denotes annual difference. Estimation is by OLS. Coefficients reported in first row and standard errors reported below in parenthesis. *** indicates significance at 99% confidence; ** at 95% confidence, and * at 90% confidence. Time fixed-effects, country fixed-effects, and robust standard errors used in both models.

Appendix B – Proof of Theoretical Model

Proof of Proposition 1

From Equations 3, 4, and 5, the first order condition of the utility maximization function for an agent with a given productivity ω with respect to $d_t(\omega)$ is:

$$\frac{1}{R_t}U'\left(c_{y,t}(\omega)\right) - \beta - \mu_d = 0$$

$$U'\left(c_{y,t}(\omega)\right) = \beta R_t + \mu_d R_t \tag{12}$$

where μ_d is the Lagrange multiplier associated with the credit constraint, $d_t(\omega) \leq \bar{d}$. Similarly, the first order condition with respect to $x_t(\omega)$ is:

$$-B_t U'\left(c_{y,t}(\omega)\right) + \beta B_{t+1} + \mu_x = 0$$

$$U'\left(c_{y,t}(\omega)\right) = \beta\frac{B_{t+1}}{B_t} + \frac{\mu_x}{B_t} \tag{13}$$

where μ_x is the Lagrange multiplier associated with the short-selling constraint $0 \leq x_t(\omega)$. This implies that for every agent:

$$U'\left(c_{y,t}(\omega)\right) = \beta\frac{B_{t+1}}{B_t} + \frac{\mu_x}{B_t} = \beta R_t + \mu_d R_t \tag{14}$$

By assumption, rich agents hold assets and do not borrow. Thus, μ_d and μ_x and are nonbinding and must be equal to zero. Equation 14 simplifies to:

$$U'\left(c_{y,t}(\omega^{high})\right) = \beta\frac{B_{t+1}}{B_t} = \beta R_t \tag{15}$$

and so in steady-state $R_t = 1$. Thus I arrive at:

$$U'\left(c_{y,t}(\omega^{high})\right) = \beta \tag{16}$$

With the assumption that rich agents hold all bubbly assets ($x_t(\omega^{high}) = 1$) and that $R_t = 1$, $U'\left(c_{y,t}(\omega^{high})\right)$ with respect to $d_t(\omega)$ for rich agents (agents with productivity ω^{high}) is simply:

$$U'\Big(c_{y,t}\big(\omega^{\text{high}}\big)\Big) = \frac{1}{\omega^{\text{high}} - \bar{d} - B_t} \tag{17}$$

which implies, by Equation 16, that:

$$\omega^{\text{high}} - \bar{d} - B_t = \frac{1}{\beta}$$

$$B_t = \omega^{\text{high}} - \bar{d} - \frac{1}{\beta} \tag{10}$$

and so B_t is increasing with the rich agents' income. That is, an increase in income concentration for the top households—and thus an increase in income inequality—leads to an increase in asset prices. Through the related literature, I assume that the increase in asset prices is concurrent with an increase in credit.

Appendix C – Replication

All results can be replicated using the data and do files located here:

https://www.dropbox.com/sh/m6ldbc6v6mwuswv/AADOZZyXXBkNjmoUL_Hi-Uhca?dl=0